The Start-Up Gap and Jobs

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Abstract

This paper uses quarterly data from the social security registry covering the full population of Belgian firms to analyze how the secular decline in the firm entry rate affects aggregate employment. To this end, we disentangle the entry margin into two channels: the overall employment of new firms (*the start-up employment*) and the share of start-up employment by sector (*the sectoral composition of start-ups*). We find that the decline in start-up employment slowed down the growth rate of aggregate employment by 26 percent over the 2009Q2 – 2017Q1 period by shifting the age distribution of firms towards older firms. The sectoral composition of start-ups accelerated the decline in the manufacturing sector and prevented the distribution sector from a potential decline, while leaving the aggregate employment unchanged.

JEL classification: L26, M13, E24, D22.
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1. Introduction

In recent years entry of new firms and the prevalence of high growth firms has been declining. Decker, Haltiwanger, Jarmin, & Miranda (2016) document declining business dynamism in the United States and suggest that it is driven by the increased product and labor market regulations. However, this pattern is not just seen in the U.S.. Bijnens & Konings (2018) document similar trends for Belgium, a small open economy with highly regulated labor markets, and suggest that global trends are at the basis of this decline.[3] Akcigit & Ates (2019) explain the declining business dynamism in the US by the declining intensity of knowledge diffusion from the frontier firms to the laggard ones.

The creation and destruction of jobs and firms facilitate the reallocation of resources from inefficient to efficient use, and hence promote aggregate growth. Therefore, this decline in business dynamism has raised concerns about its impact on productivity growth and overall macroeconomic performance (Alon, Berger, Dent, & Pugsley, 2018; Decker et al., 2017, 2018). Particularly striking has been the slowdown in firm entry during the last couple of decades. While there has been a lot of work emphasizing the role of firm entry for innovation and the process of creative destruction in general (Acemoglu & Cao, 2015; Aghion, Akcigit, & Howitt, 2014; Aghion, Blundell, Griffith, Howitt, & Prantl, 2009), little is known about how much the decline in firm entry matters for aggregate employment. In this paper we address this question using quarterly data from the social security registry covering the full population of Belgian firms for the 2009Q2 – 2017Q1 period. To this end, we disentangle the entry margin into two channels along which it affects the aggregate employment, the overall employment of new firms at the entry stage, or *the start-up employment*, and the share of start-up employment by sector, or *the sectoral composition of start-ups*.

[3] Calvino, Flavio and Criscuolo (2019) document declining business dynamism for major OECD economies and highlight that it is more pronounced in digital intensive sectors.

The first channel, the start-up employment, affects the aggregate employment directly, by creating jobs today, and indirectly, by creating jobs later on during the life-cycle of the firm. While estimating the direct effect is trivial, estimating the indirect effect requires taking into account the heterogeneity in the post-entry growth dynamics of firms. Recent literature highlights the importance of young firms for aggregate job creation (Criscuolo, Gal, & Menon, 2017; Geurts & Van Biesebroeck, 2016; Haltiwanger, Jarmin, & Miranda, 2013). In particular, young firms have higher employment growth rates and lower survival rates than their mature counterparts. Therefore, capturing this heterogeneity in the post-entry growth dynamics along the firm age dimension is relevant for estimating the indirect effect of the start-up employment on the aggregate employment.

The second channel, the sectoral composition of start-ups, affects the aggregate employment by reallocating employment across sectors. While the direct effect of this on aggregate employment is negligible, the indirect effect requires taking into account the differences in the post-entry growth dynamics of firms across sectors. Foster, Haltiwanger, & Krizan (2006) show that the retail trade sector of the US in the 1990s was very different from the manufacturing or services, because of the intensive adoption of advanced information technology. They suggest that practically all of the labor productivity growth in the retail trade sector is accounted for by more productive entering establishments replacing less productive exiting establishments. Therefore, taking into account the differences in the post-entry growth dynamics of firms across sectors is relevant for estimating the indirect effect of the sectoral composition of start-ups on the aggregate employment.

Our contribution to the literature is three fold. First, we quantify the impact of the declining start-up employment on the aggregate employment of a small open economy, Belgium. We find that the declining startup employment slowed down the growth rate of aggregate employment by 26 percent or 19 thousand lost jobs over the 2009Q2 – 2017Q1 period. This is equivalent to 1.1 percent of the aggregate employment in 2009Q2. The lost jobs are mainly due to fewer young firms creating less jobs. For the US, Pugsley & Şahin (2019) show that the declining start-up employment decreased the aggregate employment by 11.4 percent over the period of 20 years by shifting the age distribution of firms towards older firms. Not surprisingly, the impact of declining start-up employment on aggregate employment is much smaller in Belgium than in the US, since the employment share of start-ups in the US is much higher than in Belgium.

Second, we disentangle the roles of the overall start-up employment and the sectoral composition of start-ups for aggregate employment. For Belgium, we find that while the declining start-up employment had a significant impact on the aggregate employment, it had no impact on the sectoral composition of the economy. On the other hand, the sectoral composition of start-ups decreased the employment of manufacturing by 7 percent and increased the employment of distribution by 4 percent over the 2009Q2 – 2017Q1 period, while leaving the aggregate employment unchanged. The rise of employment in services is mainly driven by the post-entry growth dynamics of incumbent firms. In contrast, in the US the sectoral composition of start-ups is the main driver of the rise of services. (Dent, Karahan, Pugsley, & Şahin, 2016).

Third, we build on the framework of Pugsley & Şahin (2019) and extend it to capture the heterogeneity in firms across sectors. In particular, we decompose the evolution of aggregate employment into the parts that age distribution and sectoral composition of firms account for. Holding sectors' age-specific survival and conditional growth rates at their averages, this framework predicts well the path of aggregate employment over time through the endogenous shifts in the age distribution. Therefore, this quantitative model allows us to perform a counterfactual analysis, where we simulate different values of start-up employment and its allocation across sectors, and quantify the potential employment gains and losses. While this approach does not take into account the general equilibrium effects of the declining start-up employment, the existing literature suggests that such feedback effects are insignificant. For the U.S., Sedláček (2019) shows that the response of incumbent firms is too weak to offset the overall effect of the declining start-up employment.

The remainder of this paper is organized as follows: Section 2 describes the methodology used; Section 3 presents the details of the data; Section 4 discusses the results; and Section 5 provides the concluding remarks.

2. Methodology

In this section we present an approach to estimate the impact of declining start-up employment on aggregate employment. Intuitively, the declining start-up employment affects aggregate employment directly, by creating less jobs today, and indirectly, by creating less jobs later on during the life-cycle. While estimating the direct effect is trivial, estimating the indirect effect requires taking into account the post-entry growth dynamics of firms and their heterogeneity. We focus on the heterogeneity in the post-entry growth dynamics along the firm age and sector dimensions. Our choice of firm age is motivated by the literature on firm dynamics, where young firms experience higher employment growth rates and lower survival rates than their mature counterparts (Haltiwanger et al., 2013). We differentiate between different sectors, because firms face different competition, regulation and technology levels in different sectors. For example, the retail trade sector of the US in the 1990s was very different from the manufacturing or services, because of the intensive adoption of advanced information technology (Foster et al., 2006).

In Figure 1 we illustrate the intuition of how the entry margin affects aggregate employment. We focus on the manufacturing, services and distribution sectors. Each sector is grouped by the employment of entering firms (start-ups) and continuing firms (incumbents) based on firm age. Within incumbents we differentiate between the employment of young (5 years old or less) and mature (6 years old or above) firms. The sum of employment among all age groups and sectors is the aggregate employment. The sum of employment among all start-ups is the start-up employment. The share of start-up employment by sector is the sectoral composition of start-ups.

The dashed lines show the direction of employment flows between age groups within a sector over time. The employment within a sector-age cohort depends on the employment of the same cohort in the previous period, its survival rate and conditional employment growth rate. When holding sectors' age-specific survival and conditional growth rates at their averages, the variation in the aggregate employment comes from the variation in the current and past levels of both, the start-up employment and the sectoral composition of start-ups.

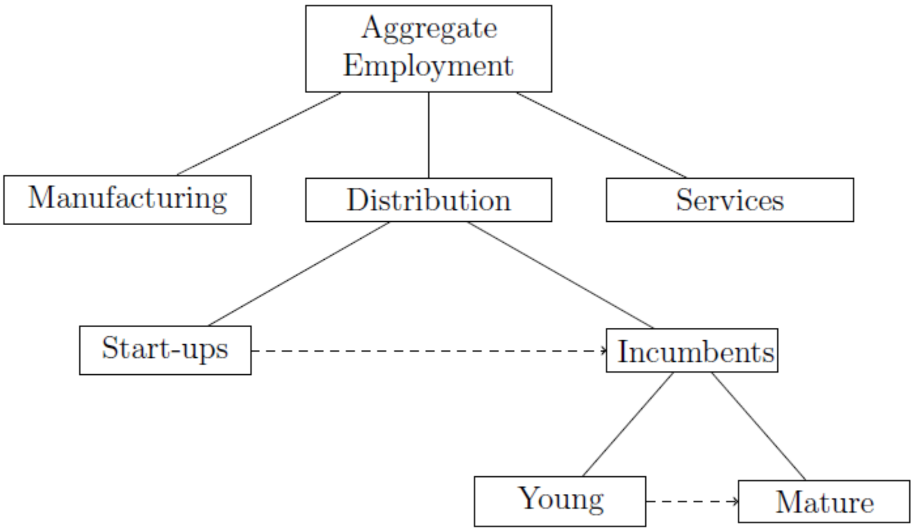

Figure 1. The diagram illustrates how the start-up employment and the sectoral composition of start-ups affect aggregate employment. Even though not shown, the manufacturing and services can be further decomposed similar to the distribution sector. The dashed lines show natural transitions of firms between the age groups due to aging. In this framework firms can either grow older or exit over time.

Formally, we build on the framework of Pugsley & Şahin (2019) and extend it to capture the heterogeneity in firms across sectors. The dynamics of aggregate employment E over time t can be written as the sum of total employment in each sector j of the economy. The aggregate employment of sector j can be split into the employment over age cohorts a. Hence, E_t is given by

$$E_t = \sum_j E_t^j = \sum_j \left(s_t^j S_t + \sum_{a>0} E_{t,a}^j \right), \tag{1}$$

where S_t is the sum of employment among firms of age zero ($a = 0$) at time t, or the start-up employment, s_t^j is the share of start-up employment in sector j at time t, or the sectoral composition of start-ups, and $E_{t,a}^j$ is the employment of age cohort a in sector j at time t. The latter term of Equation 1 can be further written as

$$E_{t,a}^j = x_{t,a}^j \left(1 + n_{t,a}^j\right) E_{t-1,a-1}^j, \tag{2}$$

where $x^j_{t,a}$ is the survival rate of firms in sector j in age cohort a over the period $t-1$ and t, $n^j_{t,a}$ is the conditional growth rate of average employment size of age cohort a over the period $t-1$ and t, and $E^j_{t-1,a-1}$ is the aggregate employment of the same cohort at time $t-1$. The product of a sector's age-specific survival and conditional growth rates is the unconditional employment growth rate of the sector's age-specific employment.

The start-up employment S_t and the sectoral composition of start-ups s^j_t provide the two channels of how start-ups affect aggregate employment. To isolate them, we replace the sector's age-specific survival and conditional growth rates with their averages ($x^j_{t,a} \equiv \bar{x}^j_a$ and $n^j_{t,a} \equiv \bar{n}^j_a$). Pugsley & Şahin (2019) show that using the sample averages of age-specific survival and conditional growth rates predicts well the evolution of trend of the aggregate employment in the US during the 1980-2010 period. This suggests that the fluctuations of $x_{t,a}$ and $n_{t,a}$ in the US were stable around their mean values. Later we show that the fluctuations of $x^j_{t,a}$ and $n^j_{t,a}$ in Belgium were stable around their mean values and that using the sample averages predicts well the evolution of trend of the aggregate employment in Belgium. Therefore, the predicted evolution of aggregate employment can be written as

$$\hat{E}_t = \sum_j \left(s^j_t S_t + \sum_{a>0} \bar{x}^j_a \left(1 + \bar{n}^j_a\right) E^j_{t-1,a-1} \right), \tag{3}$$

where $\bar{x}^j_a = \sum_{t=1}^{T} x^j_{t,a} / T$ and $\bar{n}^j_a = \sum_{t=1}^{T} n^j_{t,a} / T$.

To simplify Equation 3 we make use of the result in Geurts & Van Biesebroeck (2016), where authors show for Belgium that within age cohorts firm growth is strictly increasing with size until the age of five years, and afterwards it becomes independent of size. Therefore, we modify Equation 3 to distinguish between the firms up to the age of five years, and afterwards we group the firms that are six years old or above under the "6+" age group. Taking into account this grouping, the predicted aggregate employment can be written as

$$\hat{E}_t = \sum_j \left(s_t^j S_t + \sum_{a=1}^{5} \bar{x}_a^j (1 + \bar{n}_a^j) E_{t-1,a-1}^j + \bar{x}_{6+}^j (1 + \bar{n}_{6+}^j) \sum_{a \geq 6} E_{t-1,a-1}^j \right), \qquad (4)$$

where $\bar{x}_{6+}^j = \sum_{t=1}^{T} x_{t,6+}^j / T$ and $\bar{n}_{6+}^j = \sum_{t=1}^{T} n_{t,6+}^j / T$. Later in the article, we are going to use this framework to simulate the counterfactual evolutions of aggregate employment as the result of varying the start-up employment S_t or the sectoral composition of start-ups s_t^j.

3. Data

In this section we describe the data used for our analysis. We use quarterly data from the National Social Security Office (NSSO) of Belgium on all firms paying social security contributions during the period from 2003Q1 to 2017Q1. The data does not include self-employed people, because individual entrepreneurs report to the social security body for the self-employed, INASTI. However, it does include the people who work for self-employed. According to the estimate of the National Bank of Belgium, in the first quarter of 2017 there were 3.9 million domestic employees in Belgium, and according to the data there were 3.5 million employees. Therefore, this administrative database covers around 90 percent of all paid employment in Belgium.[4]

The data include both, actual and full-time equivalent (FTE) number of employees per firm per quarter. We use FTE number of employees as a proxy for firm size, because it captures the actual creation and destruction of jobs by firms. The measure also avoids double counting of part-time employees, who work for multiple firms. For the analysis, we focus on the manufacturing, distribution, and services sectors. These three broad sectors jointly represent 63 percent of total employment. Therefore, going forward, the aggregate employment refers to the total employment of these three sectors. The employment share by sector is relative to this aggregate employment, meaning that the three sectoral employment shares sum up to one.

	Manufacturing	Services	Distribution
NACE 2-digit code (Rev. 2)	10 – 33	57 – 82	45 – 56
Number of firms	20 475	52 225	95 770
Average firm size	22.3	10.9	6.8
Survival rate	0.983	0.979	0.974
Conditional growth rate	1.01	1.023	1.025

Table 1. The table reports summary statistics of NSSO data by sector for 2003Q1 – 2017Q1 period.

Table 1 reports summary statistics of the data by sector. On average, the manufacturing sector had the lowest number of firms and conditional growth rate, and the highest average firm size

[4] According to the estimate of the National Bank of Belgium, employees registered with the NSSO account for 85 percent of all paid employment in Belgium.

and survival rate. The distribution sector had the highest number of firms and conditional growth rate, and the lowest average firm size and survival rate.[5]

To estimate the dynamic framework we measure the evolution of the start-up employment, the sectoral composition of start-ups, and the sectors' age-specific survival rate and conditional growth rate over time. Since the data do not provide information on firm age explicitly, we infer firm entry based on the first appearance of a firm in the data set. Similarly, we infer firm exit based on the last appearance of a firm in the data set.[6] We are also interested in measuring the employment of a "true" entry rather than the employment of a "spurious" entry, such as ID change of a firm, breakup of a firm into two or more firms, merger of two existing firms or acquisition of one firm by another. Geurts (2016) and Geurts & Van Biesebroeck (2016) show that such biases result in significant distortions of the size distribution of entering firms and of the estimates of the post-entry growth dynamics of firms. Therefore, we use the shares of "spurious" entrants by size (Table 2 in Geurts, 2016) as probabilities to correct the age distribution of firms by probabilistically re-assigning the age of entering firms to $a = 6+$ based on their size.

3.1. Measuring the declining start-up employment

To measure the start-up employment S_t, we sum up the employment of all firms with $a = 0$ at time t. Figure 2 plots the evolution of the start-up employment and the employment share of start-ups over time. The solid line shows that the start-up employment has declined from 3.8 thousand jobs in 2003 to 2.6 thousand jobs in 2014. After that the start-up employment began to rise reaching 3.2 thousand jobs in 2017. The employment share of start-ups followed

[5] The time span of the data includes the revision of the NACE codes in the first quarter of 2008. While the re-classification of the sectors during the 2007Q4-2008Q1 transition may cause some distortions, for the purposes of this article it is not significant because we focus on the period after 2008.

[6] There are firms that disappear from the data and reappear after some time. After a discussion with the NSSO representative, we conclude that these instances correspond to firms with zero employment, and do not constitute firm exit.

similar path during this period. This trend is consistent with the evidence on declining business dynamism in Belgium (Bijnens & Konings, 2018).

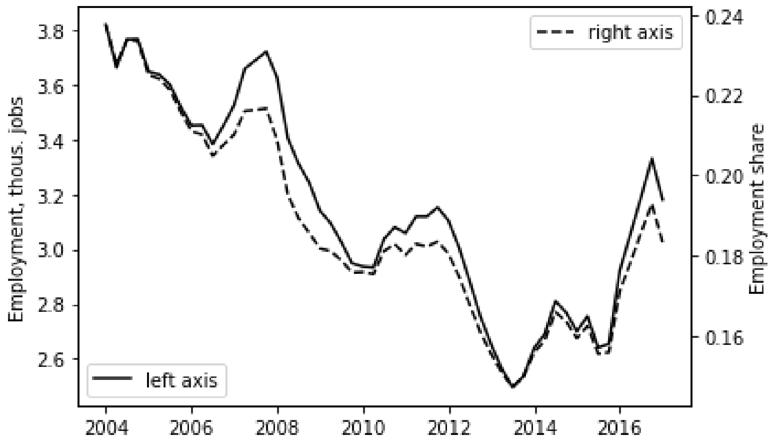

Figure 2. The figure plots the evolution of the start-up employment (the solid line) and the employment share of start-ups (the dashed line) over time in Belgium based on NSSO data. The measures are corrected for "spurious" entrants. All plotted values are 4-quarter moving averages.

Pugsley & Şahin (2019) show that the declining start-up employment caused an increase in the share of mature firms in the US over the last three decades. Figure 3 shows that the age distribution of firms in Belgium shifted towards older firms.[7] Over the 2008Q1 – 2017Q1 period the employment share of mature (ages 6+) firms increased from 92 percent to 94.5 percent. The firm share of mature firms increased from 66 to 74 percent. Therefore, we note that while the start-up employment was declining in Belgium, the share of mature firms was increasing.

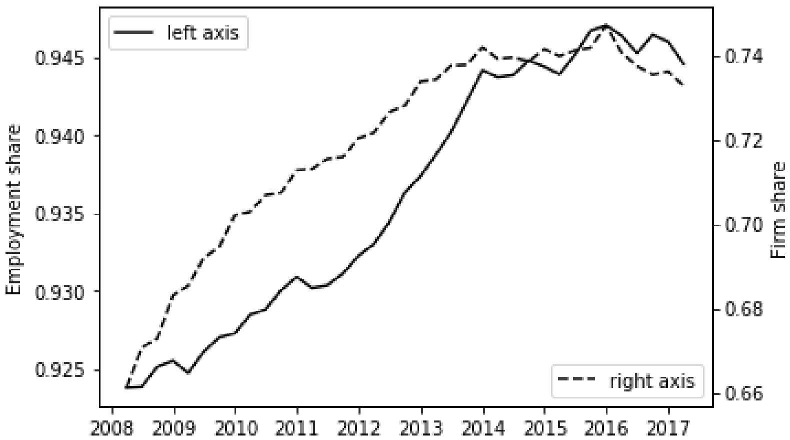

Figure 3. The figure plots the evolution of the employment share (the solid line) and the firm share (the dashed line) of mature (ages 6+) firms over time in Belgium based on NSSO data. The measures are corrected for "spurious" entrants.

[7] Since we have to track each firm for at least five years to infer its age, we are able to distinguish between young (ages 1 to 5) and mature (ages 6+) firms starting from 2008Q1 and onwards.

3.2. Measuring the sectoral composition of start-ups

To measure the sectoral composition of start-ups s_t^j we divide sectors' start-up employment by the overall start-up employment. Figure 4 plots the evolution of the sectoral composition of start-ups over time. The left panel indicates that the relative allocation of start-up employment across sectors was stable over time. On average, most of the start-up employment is allocated to the distribution sector. The least of the start-up employment is allocated to the manufacturing sector. The right panel shows that the sectoral composition of start-ups in absolute terms was declining across all sectors. This is explained by the declining start-up employment overall.

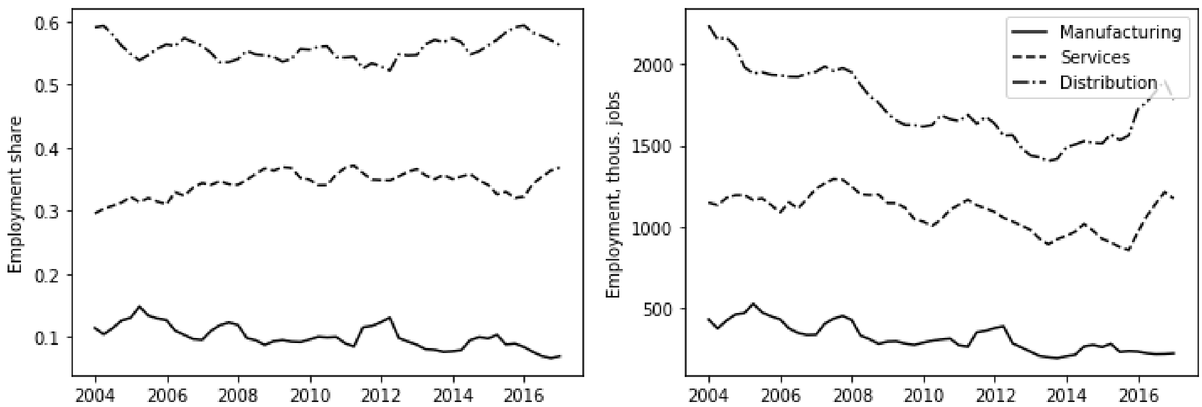

Figure 4. The figure plots the evolution of the sectoral composition of start-ups in relative (the left panel) and absolute (the right pane) terms over time in Belgium based on NSSO data. The solid, dashed and dash-dot lines correspond to the manufacturing, services and distribution sectors, respectively. The measures are corrected for "spurious" entrants. All values are plotted as a 4-quarter moving averages.

For comparison purposes, we also plot the evolution of aggregate employment by sector over time in Figure 5. On average, the distribution sector has the most of employment, and it is slowly increasing over time, in absolute and relative terms.[8] The services sector exhibit the greatest growth rate of employment over the period.[9] The employment in manufacturing was declining in absolute and relative terms. Therefore, we note that while the sectoral allocation of

[8] While there are some discontinuities in the aggregate employment during the 2007Q4-2008Q1 transition, they do not affect the trends significantly.

[9] In Appendix, subsection A1, we further decompose services by knowledge intensity to understand the rise of services and its heterogeneity.

start-up employment was stable over the period, the sectoral composition of the economy was undergoing structural transformation.

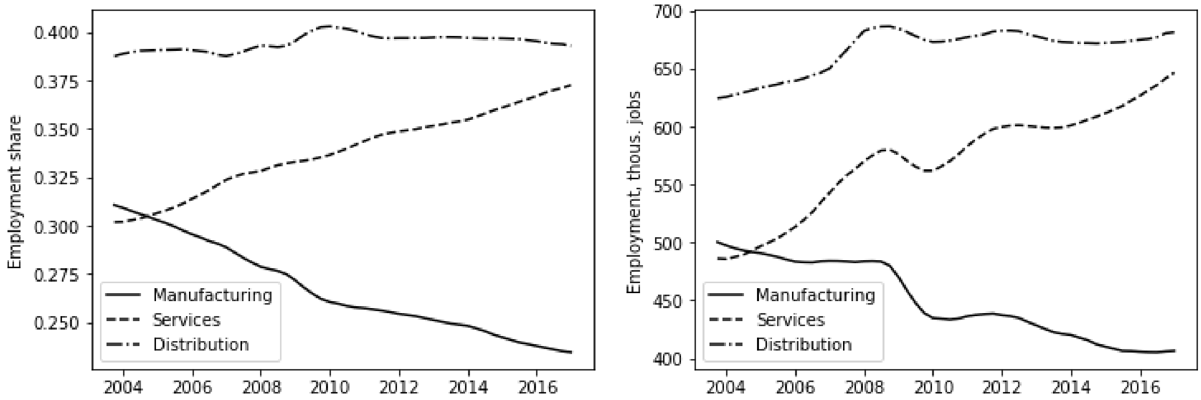

Figure 5. The figure shows the evolution of aggregate employment by sector for Belgium based on the NSSO data set. The left panel plots the evolution of employment share by sector. The right panel plots the evolution of aggregate employment by sector. The solid, dashed and dash-dot lines correspond to the manufacturing, services and distribution sectors, respectively. All values are plotted as a 4-quarter moving averages.

3.3. Measuring the sector's age-specific survival and conditional growth rates

To measure the sector's age-specific survival and conditional growth rates we discretize firm age ($a = 1, 2, 3, 4, 5, 6+$) and compute the average over time of the survival rate and the conditional growth rate for each sector-age group ($\bar{x}_a^j$ and $\bar{n}_a^j$).[10] The measures are reported in Table 2.

	Survival rate $\bar{x}_a^j$			Conditional growth rate $(1 + \bar{n}_a^j)$		
Age	Manufacturing	Services	Distribution	Manufacturing	Services	Distribution
1	0.954	0.946	0.922	1.315	1.378	1.362
2	0.959	0.956	0.942	1.061	1.092	1.057
3	0.968	0.964	0.954	1.024	1.060	1.042
4	0.972	0.970	0.961	1.022	1.046	1.032
5	0.977	0.973	0.968	1.020	1.027	1.028
6+	0.985	0.981	0.980	1.010	1.017	1.016

Table 2. The table reports the mean values of sector's age-specific survival and conditional growth rates based on the 2011Q1 – 2017Q1 period in NSSO data.

The survival rate increases with age across all sectors. The conditional growth rate decreases with age and it also holds across sectors. Between sectors, the distribution sector has the lowest survival rate and the manufacturing sector has the highest survival rate across all age groups.

[10] We use the period after 2010 to compute the sector's age-specific survival and conditional growth rates because the period before that corresponds to the financial crisis with significant fluctuations.

On the other hand, the manufacturing sector has the lowest conditional growth rate and the services sector has the highest conditional growth rate across all age groups. While the differences between the sector's age-specific survival and growth rates are small, they play a crucial role in explaining the aggregate employment dynamics of Belgium, as it will be shown later in the article.

4. Results

In this section we illustrate the role of start-ups in the aggregate employment dynamics of Belgium. In particular, we conduct a series of counterfactual simulations to isolate the channels along which start-ups affect aggregate employment. First, we investigate the role of fluctuations in the sector's age-specific survival and conditional growth rates in explaining the evolution of aggregate employment over time. As a result, we show that holding the sector's age-specific survival rate and conditional growth rate at their averages, predicts well the trend evolution of aggregate employment in Belgium. Second, we quantify the effect of the declining start-up employment on the aggregate employment. We find that the declining startup employment slowed down the growth rate of aggregate employment by 26 percent over the 2009Q2 – 2017Q1 period. We observe that the effect slowly builds up over time through having lower number of jobs among young (less than 6 years old) firms. Third, using the same period, we show that the sectoral composition of start-ups did not significantly affect the aggregate employment, but it affected the sectoral composition of economy by decreasing the employment in manufacturing by 7 percent and increasing the employment in distribution by 4 percent.

4.1. The stability of sector's age-specific survival and growth rates

To illustrate the stability of sector's age-specific survival and conditional growth rates, we perform a counterfactual simulation where we predict the aggregate employment using

$$\hat{E}_t = \sum_j \left(s_t^j S_t + \sum_{a=1}^{5} \bar{x}_a^j (1 + \bar{n}_a^j) E_{t-1,a-1}^j + \bar{x}_{6+}^j (1 + \bar{n}_{6+}^j) \sum_{a \geq 6} E_{t-1,a-1}^j \right),$$

and holding the sector's age specific survival rate and conditional growth rate at their sample averages (Table 2). The time variation in predicted aggregate employment comes from the variation in the start-up employment and the sectoral composition of start-ups, which are taken as given in the data.

In Figure 6 we plot the actual and predicted employment. We start the prediction from 2009Q2 because the aggregate employment during 2008Q1 – 2009Q1 was too volatile to start from. The solid lines plot the actual employment. The dashed lines plot the predicted employment. Given that the sample averages do not reflect the business-cycle fluctuations in the sector's age specific survival rate and conditional growth rate, the model over-predicts the employment during economic downturns and under-predicts the employment during the economic booms. Nonetheless, the baseline predictions capture well the trend evolution of aggregate employment overall and by sector.

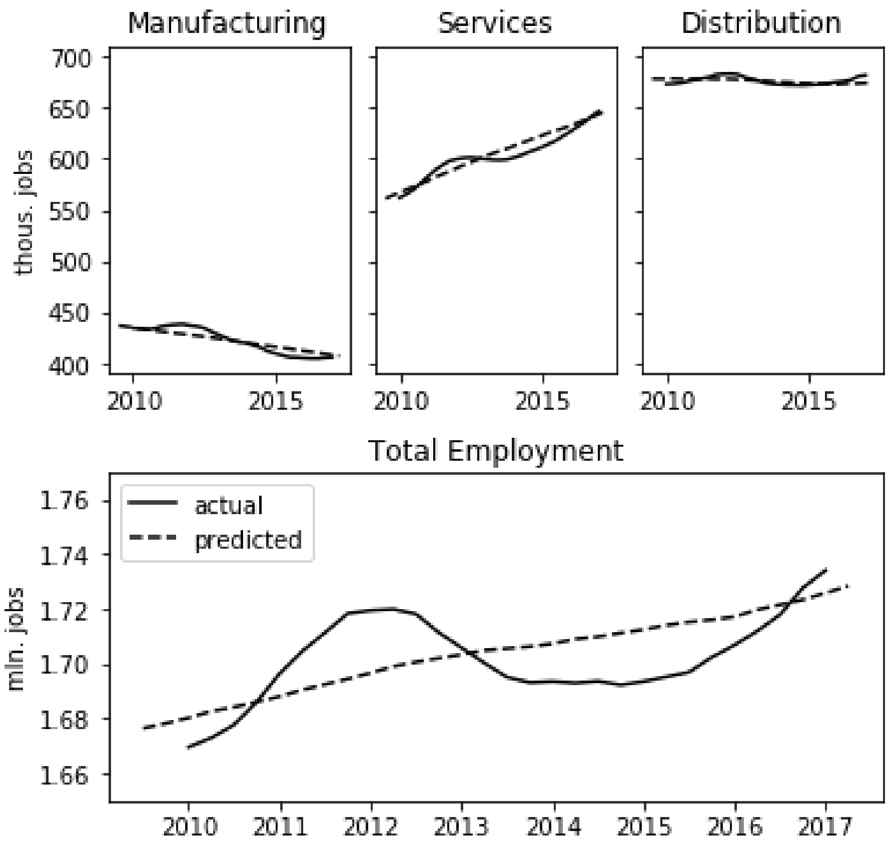

Figure 6. The figure compares the actual and predicted employment by sector and in aggregate. The prediction is based on holding the sector's age-specific survival rate and conditional growth rate at their sample averages. The solid line is the actual employment, and the dashed line is the prediction. The actual values are plotted as 4-quarter moving averages.

This suggests that in Belgium the sector's age-specific survival rate and conditional growth rate fluctuate around their mean values over time, and that these mean values are stable over time. To test the last point, we evaluate the trend component of $x_{t,a}^{j}$ and $\left(1+n_{t,a}^{j}\right)$ over time. For the hypothesis to hold, the trend component should be statistically insignificant across sectors and age groups. The results of OLS regressions are given in Table 3.

The first and third regressions consider the entire sample of the data from 2008Q1 to 2017Q1 for $x_{t,a}^{j}$ and $\left(1+n_{t,a}^{j}\right)$, respectively. Both regressions imply that the trend component is significant. The period of 2008-2010 was highly volatile in Belgium because of the financial crisis, which most likely caused too much volatility in the measure of $x_{t,a}^{j}$ and $\left(1+n_{t,a}^{j}\right)$. Therefore, in the second and forth regressions we exclude the 2008-2010 period. Now the trend component of $\left(1+n_{t,a}^{j}\right)$ is insignificant across all age groups and sectors. The trend component of $x_{t,a}^{j}$ is insignificant in manufacturing and services across all age groups, but it is significant in the distribution sector for firms above the age of 2 years. The magnitude of the coefficient is negative, which suggests that the survival rate of incumbent firms in distribution is declining over time. Such a decline is most probably driven by exogenous factors (such as the adoption of information technologies or international trade) and not by the declining number of start-ups in that sector. If anything, the declining firm entry should lead to higher survival rate among incumbents. Therefore, the evidence suggests that the linear trend components of $x_{t,a}^{j}$ and $\left(1+n_{t,a}^{j}\right)$ are not significant, and hence, the mean values of the survival and conditional growth rates are stable over time.

Similarly, Pugsley & Şahin (2019) show that the life-cycle dynamics of firms in the US remained relatively constant during the last three decades. They found that firm survival and employment growth rates conditional on age fluctuate around their mean values on aggregate, across sectors and states. Also for the US, Dent et al. (2016) show that the differences in the mean life-cycle dynamics of firms across sectors remained stable over time.

The results illustrate that in Belgium the sector’s age-specific survival rate and conditional growth rate fluctuate around stable values over time. Therefore, we use the predicted aggregate employment based on holding the sector’s age-specific survival rate and conditional growth rate at their sample as the “actual” case for counterfactual analysis in the following sections.

	Survival rate $x_{t,a}^{j}$		Conditional Growth Rate $\left(1+n_{t,a}^{j}\right)$	
	(1)	(2)	(3)	(4)
Trend	-0.0007*	-0.0007	-0.0058*	0.0037
	(0.000)	*(0.001)*	*(0.003)*	*(0.005)*
Trend	-0.0008	-0.0016	0.0111***	0.0045
* age 1 – 2 years	*(0.001)*	*(0.001)*	*(0.004)*	*(0.007)*
Trend	5.7e-05	-0.0003	0.0087**	0.0034
* age 2 – 3 years	*(0.001)*	*(0.001)*	*(0.004)*	*(0.007)*
Trend	0.0003	0.0009	0.0076*	-0.0041
* age 3 – 4 years	*(0.001)*	*(0.001)*	*(0.004)*	*(0.007)*
Trend	0.0008	0.0016	0.0059	-0.0038
* age 4 – 5 years	*(0.001)*	*(0.001)*	*(0.004)*	*(0.007)*
Trend	0.0005	0.0006	0.0073*	0.0037
* age 5 years and more	*(0.001)*	*(0.001)*	*(0.004)*	*(0.007)*
Trend * Services	-0.0007	-0.0011	0.0045	0.0063
	(0.001)	*(0.001)*	*(0.004)*	*(0.007)*
Trend * Services	0.0004	0.0013	-0.0092	-0.0119
* age 1 – 2 years	*(0.001)*	*(0.001)*	*(0.006)*	*(0.010)*
Trend * Services	-1.8e-05	0.0006	-0.0068	-0.0148
* age 2 – 3 years	*(0.001)*	*(0.001)*	*(0.006)*	*(0.010)*
Trend * Services	-0.0003	-0.0014	-0.0034	-0.0018
* age 3 – 4 years	*(0.001)*	*(0.001)*	*(0.006)*	*(0.010)*
Trend * Services	-0.0005	-0.0015	-0.0034	-0.0034
* age 4 – 5 years	*(0.001)*	*(0.001)*	*(0.006)*	*(0.010)*
Trend * Services	0.0003	0.0004	-0.0041	-0.0046
* age 5 years and more	*(0.001)*	*(0.001)*	*(0.006)*	*(0.010)*
Trend * Distribution	-0.002***	-0.0034***	0.0128***	0.004
	(0.001)	*(0.001)*	*(0.004)*	*(0.007)*
Trend * Distribution	0.0014*	0.0031**	-0.0155***	-0.0087
* age 1 – 2 years	*(0.001)*	*(0.001)*	*(0.006)*	*(0.010)*
Trend * Distribution	0.0006	0.0017	-0.0128**	-0.008
* age 2 – 3 years	*(0.001)*	*(0.001)*	*(0.006)*	*(0.010)*
Trend * Distribution	0.0008	0.0008	-0.0115*	0.0004
* age 3 – 4 years	*(0.001)*	*(0.001)*	*(0.006)*	*(0.010)*
Trend * Distribution	0.0005	-0.0001	-0.0105*	-0.0016
* age 4 – 5 years	*(0.001)*	*(0.001)*	*(0.006)*	*(0.010)*
Trend * Distribution	0.0015*	0.0024	-0.0133**	-0.0032
* age 5 years and more	*(0.001)*	*(0.001)*	*(0.006)*	*(0.010)*
Period	2008 – 2017	2011 – 2017	2008 – 2017	2011 – 2017
N	648	450	648	450
R2	0.863	0.859	0.887	0.895

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. OLS regressions estimate the linear trend in survival rates and conditional employment growth rates by age and sector. Survival rate is fraction of sector-age cohort that survived from previous quarter. Conditional employment growth rate is the growth rate of cohort's average employment size. All specifications control for quarter, sector and age fixed effects. Only coefficients of interest are included in the table.

4.2. The impact of the declining start-up employment

To illustrate the impact of the declining start-up employment on the aggregate employment, we run the following counterfactual simulation. We modify the baseline model (4) by replacing the actual start-up employment S_t with a counterfactual start-up employment S_t^{cf}, which starts as the average of the actual start-up employment in 2009Q2 – 2010Q1 but continues to grow over time at an annual rate of 2 percent (0.4963 percent per quarter). The growth rate of 2 percent is chosen in order to mimic and maintain the start-up employment that we observe in the pre-crisis period.

The first panel of Figure 7 plots the actual start-up employment (the solid line) and the counterfactual start-up employment (the dashed line) over time. While the actual start-up employment continues to decline in 2012 and picks up in 2014, the counterfactual start-up employment continues to grow steadily at a constant pace of 2 percent per year. The difference between two lines is the direct effect of the declining start-up employment on the aggregate employment, which is about 500 jobs per quarter or 2,000 jobs per year. The direct impact already becomes significant for a small economy such as Belgium. The accumulated number of lost jobs over the 2009Q2 – 2017Q1 period sums up to 8,800 jobs, and it does not take into account the jobs due to the post-entry growth dynamics of potentially lost entrants.

To estimate the overall effect of the declining start-up employment on the aggregate employment we predict the new evolution of aggregate employment $\widetilde{E}_t$ using

$$\tilde{E}_t = \sum_j \left(s_t^j S_t^{cf} + \sum_{a=1}^{5} \bar{x}_a^j (1 + \bar{n}_a^j) \tilde{E}_{t-1,a-1}^j + \bar{x}_{6+}^j (1 + \bar{n}_{6+}^j) \sum_{a \geq 6} \tilde{E}_{t-1,a-1}^j \right)$$

and compare it to the actual (or the baseline) evolution of aggregate employment $\hat{E}_t$ predicted using (4). The difference between the actual and predicted aggregate employment accounts for the declining start-up employment in the past, taking into account the cumulative indirect effects.

The second panel of Figure 7 plots the actual aggregate employment (the solid line) and the predicted aggregate employment (the dashed line) based on the counterfactual start-up employment. The difference between the two lines grows over time and reaches almost 19 thousand jobs in 2017Q1. Therefore, on average every additional start-up creates 2.2 jobs net in the next 8 years of their life-cycle.[11] In terms of employment, the declining start-up employment decreased the aggregate employment by 1.1 percent relative to the predicted aggregate employment in 2017Q1. In terms of growth, the growth rate of aggregate employment slowed down by 26 percent over the 2009Q2 – 2017Q1 period.

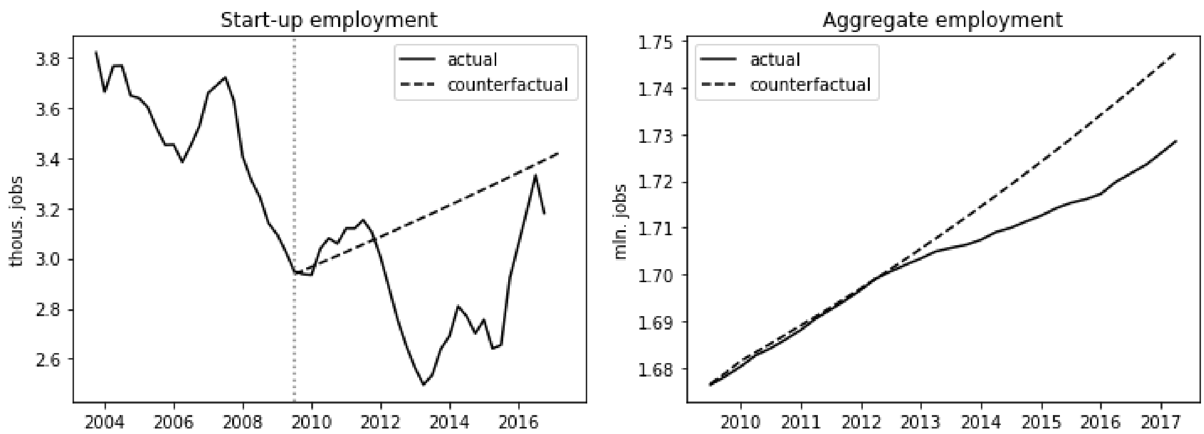

Figure 7. The figure compares the actual employment with the predicted employment based on the counterfactual start-up employment. The left panel plots the start-up employment. The actual start-up employment is plotted as a 4-quarter moving average with the solid line. The counterfactual start-employment is plotted with the dashed line and starts as the actual start-up employment in 2009Q2 but continues to grow at an annual rate of 2 percent. The right panel plots the aggregate employment. The solid line is the actual aggregate employment based on holding the sector's age-specific survival rate and conditional growth rate at their sample averages and using the actual start-up employment. The dashed line is the counterfactual aggregate employment based on the counterfactual start-up employment.

Within young firms (ages < 6), the gap between the actual and predicted aggregate employment reaches 18,300 jobs in 2017Q1, which is about 96 percent of the total number of lost jobs due to the declining start-up employment. This illustrates how the declining start-up employment shifts the employment towards older firms. Interestingly, the emerged employment gap will persist over time even if the actual start-up employment also continues to grow at 2 percent per year after 2017. In the literature this effect is known as a "lost generation

[11] This is a rough estimate obtained by dividing the total number of lost jobs due to the declining start-up employment (19,000 jobs) by the total number of lost start-ups (8,800 start-ups). Since the average size of a start-up upon entry is 1, therefore 8,800 start-ups is equivalent to 8,800 jobs.

of firms”, which has a limited short run impact but persistent long run effect on employment (Sedláček, 2019).

Table 4 shows the percent change of aggregate employment over the period from 2009Q2 to 2017Q1 for the actual and counterfactual cases. In both cases, the employment decreases in manufacturing and increases in services. The magnitude of changes is slightly different, the decline in manufacturing happens faster in the actual case and the increase in services is more rapid in the counterfactual case. The distribution sector is different. While the aggregate employment of distribution sector went down by half a percentage point in the actual case, it went up by almost a percentage point in the counterfactual case. This is explained by the low survival rate of incumbent firms in the distribution sector. Nonetheless, the sectoral composition of economy stays relatively unchanged.

	The percent change of aggregate employment	
	Actual	Counterfactual
Manufacturing	-6.75%	-6.39%
Services	15.22%	16.54%
Distribution	-0.56%	0.88%
Total	3.11%	4.23%

Table 4. The table shows the percent change of aggregate employment by sector and overall over the 2009Q2 – 2017Q1 period for the actual case and the counterfactual case, where the start-up employment grows at the annual rate of 2%.

In Appendix (subsection A4), we show a sensitivity analysis exploring various counterfactual scenarios for the start-up employment. The result remains robust, the declining start-up employment has a significant and persistent effect on the aggregate employment.

4.3. The impact of the sectoral composition of start-ups

To illustrate how does the sectoral composition of start-ups affects aggregate employment, we simulate another counterfactual scenario where the sectoral allocation of start-up employment is held fixed and proportional to the distribution of total employment across sectors. This approach is based on the idea of misallocation and a subsequent change in aggregate employment through the sectoral differences in sector’s age-specific survival and conditional growth rates. If the actual allocation of start-up employment across sectors is efficient, then any other allocation is inefficient. The difference in the evolution of aggregate employment between the two simulations is the gain due to efficient allocation of start-up employment across sectors.

We modify the baseline model (4) by replacing the actual sectoral allocation of start-up employment s_t^j with a counterfactual start-up employment s_{cf}^j, which we set to the average employment share of sector j during the 2009Q2 – 2010Q1 period $\left(s_{cf}^j = \bar{e}_{2009}^j\right)$, and predict the new evolution of aggregate employment $\widetilde{E}_t$ using

$$\tilde{E}_t = \sum_j \left(s_{cf}^j S_t + \sum_{a=1}^{5} \bar{x}_a^j \left(1 + \bar{n}_a^j\right) \tilde{E}_{t-1,a-1}^j + \bar{x}_{6+}^j \left(1 + \bar{n}_{6+}^j\right) \sum_{a \geq 6} \tilde{E}_{t-1,a-1}^j \right)$$

and compare it to the actual (or the baseline) evolution of aggregate employment $\hat{E}_t$ predicted using (4).

Figure 8 plots the evolution of actual and counterfactual scenarios. The solid lines in the upper three panels display the actual sectoral allocation of start-up employment. The dashed lines plot the counterfactual sectoral allocation of start-up employment. While the actual shares do fluctuate over time, their trend evolution was flat over the 2009Q2 – 2017Q1 period. The counterfactual share of start-up employment is higher in manufacturing and lower in distribution than the actual share of start-up employment. Comparing the actual and counterfactual cases is similar to evaluating the sectoral job reallocation through entry margin.

To see the impact on aggregate employment, we plot the evolution of aggregate employment by sector in the lower three panels of Figure 8. The solid and dashed lines correspond to the actual and predicted values, respectively. While the actual employment in manufacturing was decreasing, the predicted employment in manufacturing was flat over the 2009Q2 – 2017Q1 period. On the other hand, the actual employment in distribution was relatively flat, while the predicted employment in distribution was decreasing. In services, both, the actual and predicted evolution of aggregate employment were increasing with the predicted employment slightly lagging behind. Similarly, the evolution of the overall employment did not change significantly. This suggests that the start-up jobs lost in manufacturing are compensated by the new jobs in distribution.

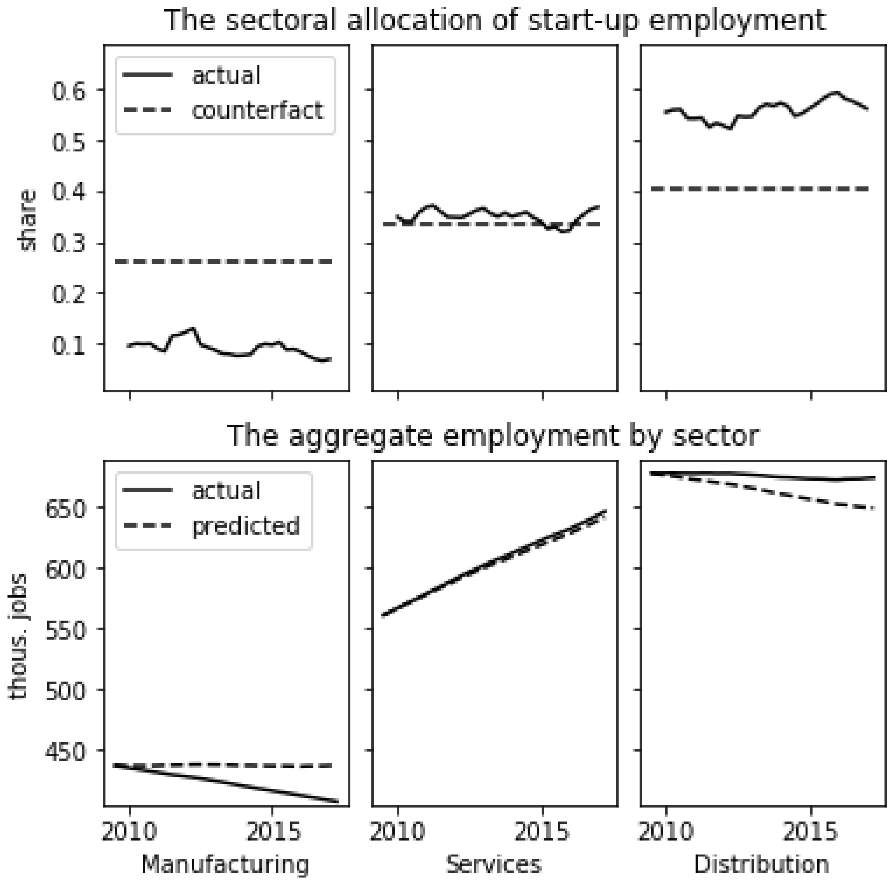

Figure 8. The figure displays the results of the counterfactual exercise where we hypothetically keep the sectoral composition of start-ups fixed and proportional to the sectoral composition of economy in 2009. The upper three panels plot the actual (the solid lines) and counterfactual (the dashed lines) sectoral allocation of start-up employment by sector. The lower three panels plot the evolution of actual (the solid lines) and predicted (the dashed lines) employment by sector. The actual sectoral allocation of start-up employment is plotted as a 4-quarter moving average.

To quantify the results of the simulation, we display the percent change of aggregate employment for the actual and counterfactual scenarios in Table 5. The first column shows the percent change of actual aggregate employment over the 2009Q2 – 2017Q1 period. The second column shows the percent change of predicted aggregate employment over the same period. The actual employment in manufacturing goes down by 6.7 percentage points more than the counterfactual one. On the other hand the actual employment in distribution goes down by 3.6

percentage points less than the counterfactual one. In services, both, the actual and counterfactual employment increase by the same order of magnitude.

	The percent change of aggregate employment	
	Actual	Counterfactual
Manufacturing	-6.75%	-0.04%
Services	15.22%	14.43%
Distribution	-0.56%	-4.18%
Total	3.11%	3.13%

Table 5. The table shows the percent change of aggregate employment by sector and overall over the 2009Q2 – 2017Q1 period for the actual case and the counterfactual case, where the sectoral composition of start-ups is fixed and proportional to the sectoral composition of economy.

The results of the simulation suggest that the sectoral composition of start-ups did not affect the overall employment significantly, but significantly changed the sectoral composition of economy by decreasing the employment share of manufacturing and preventing the distribution sector from a bigger decline.

5. Conclusion

In this paper we examine the role of start-ups in the aggregate employment dynamics of Belgium. In particular, we analyze the two channels along which start-ups affect aggregate employment: the start-up employment and the sectoral composition of start-ups. To this end, we decompose the evolution of aggregate employment by sector and age, and run a series of counterfactual simulations.

The first channel illustrates that the declining start-up employment slowed down the growth rate of aggregate employment by 26 percent over the 2009Q2 – 2017Q1 period by shifting the age distribution of firms towards older and slower growing firms. Based on our data this represents 19 thousand lost jobs over 8 years and the majority of these jobs are among young firms. The emerged employment gap persistently grows over time. This suggests that the secular decline in firm entry observed in Belgium has a significant and growing effect of dampening the aggregate employment growth.

The second channel shows that the sectoral composition of start-ups did not affect the overall employment growth of Belgium. However within sectors, the sectoral composition of start-ups plays a crucial role for maintaining the size of the distribution sector by reallocating the employment from manufacturing to distribution and services. The rise of employment in services is mainly driven by the growth dynamics of incumbent firms.

We confirm the importance of supporting firm entry as it has positive and significant effect on aggregate employment growth. On average every additional start-up in Belgium creates 2.2 jobs net in the following 8 years of its life-cycle. Therefore, government regulations need to focus on eliminating administrative entry barriers to the creation of new firms across all sectors. We highlight the heterogeneity in post-entry growth dynamics of start-ups between different sectors and suggest that detailed sectoral analysis would offer additional insights for the direction of structural changes, which have implications to skills and infrastructure related policies.

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Appendix

A1. Understanding the rise of services and its heterogeneity

Differentiating the distribution sector from the services sector highlighted the differences in employment dynamics between the two sectors. Young firms in services have higher survival and conditional employment growth rates than young firms in distribution. Within services we can further differentiate between more and less knowledge intensive firms. We use average firm wages as a proxy for knowledge intensity. Using this proxy suggests that firms which pay higher average wages are more knowledge intensive.

We split the services sector into two segments, high and low knowledge intensity segments. The NSSO data include total gross wage per firm per quarter. We compute average gross wages per FTE per quarter by dividing total gross wages by FTE number of employees. Table 6 reports summary statistics of the data on services by knowledge intensity.

	Services – High	Services – Low
NACE 2-digit code (Rev. 2)	58 – 63, 64 – 66, 69 – 75	68, 77 – 82
Number of firms	33,643	18,387
Average firm size	9.9 FTE	14.5 FTE
Wage / FTE / quarter	9,003.24 EUR	6,735.32 EUR

Table 6. The table reports summary statistics of NSSO data on services by knowledge intensity for 2008Q1 – 2017Q1 period.

High-knowledge intensive services include information and communication activities, financial and insurance activities, and professional and technical activities. Low-knowledge intensive sectors include administrative and support activities. While there are more high-knowledge intensive firms, on average they are smaller in size than low-knowledge intensive firms. On the other hand, high-knowledge intensive firms pay 30 percent higher wages than their low-knowledge intensive counterparts.

Figure 9 plots the evolution of sectoral composition of services by knowledge intensity. The manufacturing and distribution sectors are not shown for convenience. The solid line plots the evolution of employment share of high- and low- knowledge intensity services. While the employment share of high-knowledge intensity services remained stable around 20 percent, the employment share of low-knowledge intensity services has increased from 14 to 18 percent of the economy during the 2008 – 2017 period. The dashed line plots the share of start-up employment by knowledge intensity of services. There is more entry in high-knowledge services with 24 percent of start-up employment than in low-knowledge intensity services with 12 percent of start-up employment.

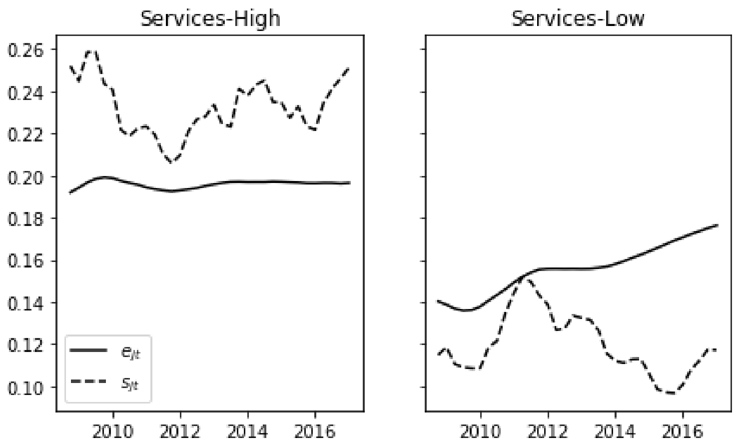

Figure 9. The figure plots the evolution of sectoral composition of services by knowledge intensity. The solid line plots the employment share of services by knowledge intensity. The dashed line plots the share of start-up employment by knowledge intensity. The manufacturing and distribution sectors are not shown in the figure.

Table 7 reports the mean values of services' age-specific survival and conditional growth rates by knowledge intensity. The survival rate of young high-knowledge intensity services is higher than the survival rate of young low-knowledge intensity services. The conditional growth rate of low-knowledge intensity services is higher than the conditional growth rate of high-knowledge intensity services regardless of age. The evidence suggests that the rise of services is driven by the high conditional growth rate of low-knowledge intensity firms and the high survival rate of young high-knowledge intensity firms.

	Survival rate $\bar{x}_a^j$		Conditional growth rate $(1+\bar{n}_a^j)$	
Age	Services – High	Services – Low	Services – High	Services – Low
1	0.950	0.938	1.333	1.454
2	0.959	0.949	1.073	1.119
3	0.967	0.958	1.049	1.073
4	0.973	0.964	1.039	1.055
5	0.975	0.970	1.029	1.026
6+	0.981	0.981	1.015	1.021

Table 7. The table reports the mean values of services' age-specific survival and conditional growth rates by knowledge intensity segment based on the 2011Q1-2017Q1 period in NSSO data.

A2. Robustness of the average survival and conditional growth rates

To evaluate the time variation of the average survival and conditional growth rates, we measure the mean values of sector's age-specific survival and conditional growth rates on subsamples, 2011 – 2013 vs 2014 – 2016. This corresponds to twelve observations for each subsample. Table 8 reports the mean values of sector's age-specific survival rates by subsample. The survival rate increases with age across all sectors and time periods. While there are some differences across time periods, there is not enough evidence to suggest that these differences are statistically different from zero. Based on point estimates, the survival rate before 2014 was slightly higher than after 2014. However these differences are not economically significant.

x_a^j	Manufacturing		Services		Distribution	
Age	2011 – 2013	2014 – 2016	2011 – 2013	2014 – 2016	2011 – 2013	2014 – 2016
1	0.952	0.956	0.947	0.946	0.927	0.920
2	0.963	0.957	0.958	0.954	0.945	0.941
3	0.969	0.968	0.966	0.963	0.957	0.953
4	0.970	0.973	0.973	0.967	0.964	0.960
5	0.976	0.978	0.975	0.972	0.972	0.966
6+	0.985	0.985	0.983	0.980	0.981	0.979

Table 8. The table reports the mean values of sector's age-specific survival rates computed on subsamples, 2011 – 2013 vs 2014 – 2016, based on the NSSO data.

Table 9 reports the mean values of sector's age-specific conditional growth rates by subsample. The conditional growth rate decreases with age across all sectors and time periods. While there are some differences across time periods, there is not enough evidence to suggest that these differences are statistically different from zero. Based on point estimates, the conditional growth rate before 2014 was lower than after 2014. This could be due to business cycle fluctuations of the economy during the 2011 – 2014 period.[12] This is in line with the observation of Pugsley & Şahin (2019). The authors show that the deviations of the mean survival and conditional growth rates from the means are correlated with the business cycle

[12] According to the National Bank of Belgium the GDP growth of Belgium during the 2012 – 2013 period was near zero and even negative in the first quarter of 2013.

fluctuations. These suggests that taking longer samples is necessary to capture “true” survival and conditional growth rates.

$\bar{n}_a^j$	Manufacturing		Services		Distribution	
Age	2011 – 2013	2014 – 2016	2011 – 2013	2014 – 2016	2011 – 2013	2014 – 2016
1	0.316	0.322	0.378	0.350	0.353	0.371
2	0.045	0.075	0.089	0.094	0.052	0.062
3	0.007	0.039	0.059	0.060	0.036	0.048
4	0.025	0.021	0.032	0.060	0.025	0.041
5	0.018	0.023	0.024	0.028	0.023	0.034
6+	0.009	0.010	0.014	0.022	0.014	0.018

Table 9. The table reports the mean values of sector’s age-specific conditional growth rates computed on subsamples, 2011 – 2013 vs 2014 – 2016, based on the NASSO data.

A3. The survival and conditional growth rates, Young vs Mature vs Old

To understand the heterogeneity in growth dynamics of mature firms (ages 6+), we further segment mature firms. Here we differentiate between young (ages 1 – 5), mature (ages 6 – 10) and old firms (ages 11+). Since we don’t have the data on firm age explicitly, we infer firm age implicitly by tracking each for at least 10 years. This way we are able to distinguish between young, mature, and old firms starting from 2013Q1 and onwards. Table 10 reports the mean values of sector’s age-specific survival and conditional growth rates.

	Survival rate $\bar{x}_a^j$			Conditional growth rate $(1+\bar{n}_a^j)$		
Age	Manufacturing	Services	Distribution	Manufacturing	Services	Distribution
1 – 5	0.967	0.962	0.949	1.078	1.087	1.092
6 – 10	0.982	0.978	0.973	1.018	1.025	1.021
11+	0.986	0.982	0.981	1.010	1.020	1.015

Table 10. The table reports the mean values of sector’s age-specific survival and conditional growth rates based on the 2013Q1 – 2017Q1 period in the NSSO data.

The survival rate of firms increases with age and this pattern holds across sectors on average. The difference in survival rates between young and mature firms is significantly higher than the difference in survival rates between mature and old firms. The conditional growth rate of firms decreases with firm age and this pattern holds across all sectors. Similarly, the difference between young and mature firms is significantly higher than the difference between mature and old firms. This suggests that the differences in growth dynamics of mature and old firms are not very significant compared to the differences in growth dynamics of young and mature firms.

This empirical observation is in line with Geurts & Van Biesebroeck (2016), where the authors using the data on Belgian firms show that the post-entry growth dynamics of firms are increasing with firm size until the age of five. For firms older than five years, firm growth follows the Gibrat's law where size and growth are independent (Lawless, 2014).

A4. The impact of the declining start-up employment – sensitivity analysis

While in the main analysis we compare the linearly increasing start-up employment at 2 percent a year with the actual start-up employment, here we explore the importance of non-declining start-up employment. To this end, we fit a straight line through the actual start-up employment to estimate the trend and compute the resulting aggregate employment based on the fitted start-up employment. After that we reverse the declining start-up employment trend and compute the new aggregate employment based on the reversed start-up employment. We explore two scenarios for reversing the trend, constant and increasing start-up employment.

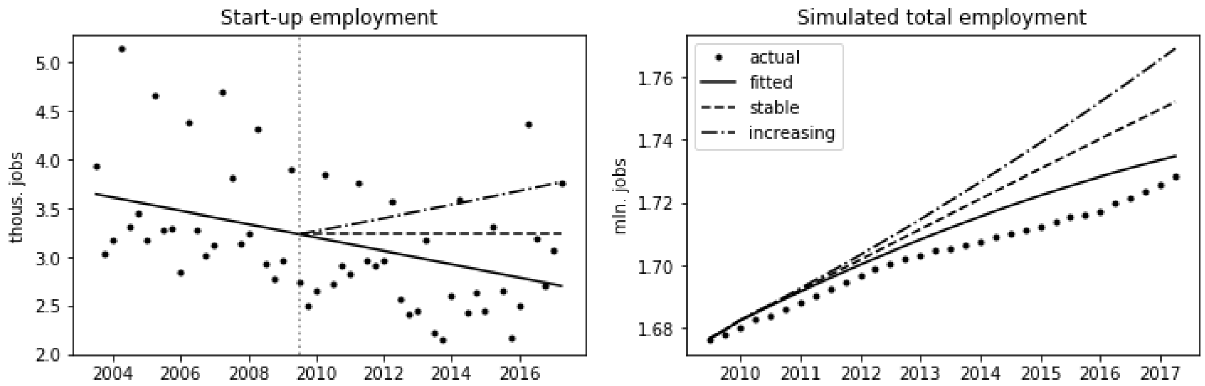

Figure 10. The figure plots the evolution of aggregate employment based on the different evolutions of start-up employment. The left panel plots the start-up employment. The dots plot the actual start-up employment observed in the NSSO data. The solid line plots a fitted line over time. Starting from 2009Q2, the dashed and dash-dot lines plot the stable and increasing start-up employment scenarios, respectively. The right panel plots the simulated total employment as a function of start-up employment scenarios.

The left panel of Figure 10 plots the actual start-up employment (the dots) measured in the NSSO data and the counterfactual scenarios for the start-up employment. The straight solid line plots the fitted line based on the point estimates of actual start-up employment over time. The line is downward sloping confirming the secular decline of start-up employment in Belgium. Starting from 2009Q2, we consider two counterfactual scenarios, stable start-up employment (the dashed line) and increasing start-up employment (the dash-dot line). Both of the counterfactual scenarios for start-up employment initiate of the fitted value of start-up employment in 2009Q2.

The right panel of Figure 10 plots the simulated aggregate employment using

$$\tilde{E}_t = \sum_j \left(s_t^j S_t^{cf} + \sum_{a=1}^{5} \bar{x}_a^j \left(1 + \bar{n}_a^j\right) \tilde{E}_{t-1,a-1}^j + \bar{x}_{6+}^j \left(1 + \bar{n}_{6+}^j\right) \sum_{a \geq 6} \tilde{E}_{t-1,a-1}^j \right),$$

where S_t^{cf} is the start-up employment corresponding to each of the scenarios aforementioned. The dots plot the evolution of simulated aggregate employment based on the actual start-up employment. The solid line plots the evolution of simulated aggregate employment based on the fitted start-up employment. The dashed line plots the evolution of simulated aggregate employment based on the counterfactual stable start-up employment. The dash-dot line plots the evolution of simulated aggregate employment based on the counterfactual increasing start-up employment.

Table 11 reports the percent change of aggregate employment over the 2009Q2 – 2017Q1 period for different scenarios of start-up employment. For the stable start-up employment case, the aggregate employment is predicted to grow by 1 percentage point more when comparing to the linearly declining start-up employment case. The difference between the actual and fitted cases, suggests that even short-term declines in the start-up employment have persistent effect on the aggregate employment.

The percent change of aggregate employment			
Actual	Fitted	Stable	Increasing
3.11%	3.45%	4.48%	5.50%

Table 11. The table reports the percent change of aggregate employment over the 2009Q2 – 2017Q1 period for different scenarios of start-up employment.